

# Location-centric Approach for Collaborative Target Detection, Classification, and Tracking

Parameswaran Ramanathan, University of Wisconsin, Madison, parmesh@ece.wisc.edu

## I. INTRODUCTION

Sensor networks consist of a large number of low cost wireless devices that are densely distributed over a geographic region of interest. Each device typically has multiple sensing modalities to monitor spatio-temporal events of interest and collect pertinent information from its perspective. Due to its inherent distributed nature, the collective information from all the devices promises an unprecedented picture of the operating environment that is very difficult to obtain using conventional centralized approaches. They have been envisioned for a broad range of applications including environment monitoring (e.g., security breaches, disaster relief), infrastructure integrity (e.g., power grid and highways), and military applications (e.g., target detection, classification, and tracking).

However, there are many challenges that must be overcome before sensor networks can be effectively deployed in practice. Foremost among them are:

1. **Lack of simple, flexible programming abstraction:** Each sensor device by itself often cannot provide useful information without collaboration with other devices. At the same time, due to the large ad hoc nature of sensor networks, it is a formidable challenge for a programmer to develop efficient distributed algorithms and implementations without a simple, but flexible, programming model.
2. **Need for energy and bandwidth efficient collaborative signal processing algorithms:** Each device is likely to have very limited energy and bandwidth capabilities to communicate with other devices. Therefore, any distributed computation on the sensor network must be very efficient in utilizing the limited power and bandwidth budget of the sensor devices.
3. **Robustness to sensor device failures:** Due to the harsh conditions in which sensor devices may be deployed, and the way in which the devices may be deployed, one can expect a significant fraction of the devices to be either non-operational or malfunctioning. Therefore, the underlying algorithms must be robust to a large number of device failures.

This paper describes an approach called *Location-centric Computing* being pursued by a team of researchers at University of Wisconsin-Madison to address the above

three challenges. This approach was evaluated using data collected from a sensor network field test at 29 Palms Marine Base in California. The paper also contains example results from this evaluation demonstrating the effectiveness of the approach.

## II. LOCATION-CENTRIC COMPUTING

The location-centric computing approach is based on the premise that sensor network applications typically require collaboration among devices in a certain area and not among an arbitrarily specified set of devices. For example, application queries such as what is the concentration profile of a certain bio-chemical agent in a given area, or what is the temperature or pressure variation in a given area, or have there been any unauthorized entries into a given area, all require collaboration among sensor devices in the area of interest as opposed to collaboration among a given set of devices.

Note that this is fundamentally different from the conventional node-centric approach in which the information exchange and collaboration is between a certain set of devices. Even if the devices move the collaboration typically continues between the same set of devices. In contrast, in the location-centric approach, a device ceases (begins) to participate in an ongoing collaboration if it leaves (enters) the corresponding defining region.

At University of Wisconsin, Madison, we recently proposed a network application programmers interface called UW-API that is particularly well suited for the location-centric computing approach [1,2,3]. In UW-API, geographic regions play the role of a node in the traditional network interface. In particular, the nodes/devices are not individually addressable in UW-API. Instead, the programmer creates entities called *regions*, which are then addressable in the communication primitives.

A region in UW-API represents a rectangular geographic area. We assume that each device is aware of its geographic location and the regions to which it belongs. Within each region, an area is designated as a *manager sub-region*. A region is typically tasked with one or more collaborative signal processing (CSP) activities. Devices in a region participate in the information exchange and collaboration signal processing activities of that region. The devices in the manager sub-region also coordinate information exchange activities needed for the CSP.

In addition to primitives for creating and deleting regions, UW-API has primitives for sending task and information to regions, receiving task and information from regions, and aggregating information within a region. These primitives are supported by an underlying location-aware routing scheme called UW-routing [1,2,3]. The routing scheme is bandwidth efficient in delivering information from one region to another. We contend that these primitives provide a simple and flexible programming abstraction for writing CSP applications in sensor networks. We have successfully used these primitives for a collaborative target tracking application.

### III. TARGET TRACKING APPLICATION

In this application, the sensor network is tasked to detect the presence of a certain type of ground vehicle and track its movement through the sensor field. The application works as follows. Regions are first created around potential target entry area. Only devices in these initial regions are active. All other devices passively wait to be activated by initial regions. Within a region the following software modules are used to detect, classify, and track a target of interest.

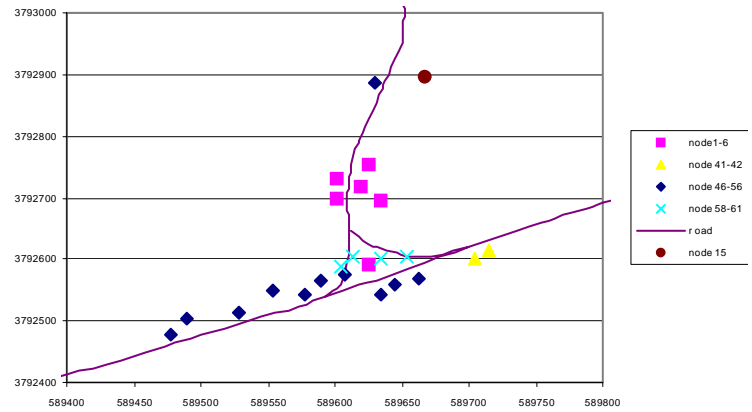
- *NodeDet*: Devices run a Constant False Alarm Rate Energy Detector for detecting the presence of a target. The devices in a region relay their decisions to the manager sub-region.
- *DetFus*: The devices in the manager sub-region run a robust fusion algorithm to combine the detection decisions of the devices in the region to arrive at consensus detection decision for the region.
- *NodeClass*: When *NodeDet* in a device decides a target is present, it invokes a classifier to determine whether the target is of the desired type. The classification result is relayed to the manager sub-region.
- *ClassFus*: When *DetFus* decides that a target is present it invokes a robust fusion algorithm to combine the classification decisions of the devices in the region to decide whether the target is of the desired type.
- *TarLoc*: When *ClassFus* decides that the target is of the desired type, it invokes a localization algorithm to estimate the target's location.
- *TarTrak*: Devices in the manager sub-region estimate target parameters such as speed and direction and use it to predict the near-term target locations. If the predicted target locations lie outside the region, additional regions are created and tasked with the application.

### IV. EXAMPLE RESULTS

A preliminary implementation of the above target tracking application was field tested at 29 Palms Marine Base in November 2001. The sensor network for the field test

consisted of 70 WINS2.0 devices from Sensoria Corporation. Each device was equipped with three sensing modalities: acoustic, passive infrared, and seismic. The network was used to track military vehicles such as AAV, DW, LAV, and HMVVV. Sensing data was also collected or later use during the field test.

Since the field test, we refined the underlying algorithms in the above application. We also developed a mechanism to playback the data collected during the field test. Using the timestamps in the collected data, the playback mechanism emulates the field test on a sensor network testbed at BBN Technologies. That is, an application running on the BBN testbed completely emulates the performance at the 29 Palms field test. We evaluated our target tracking application using this playback mechanism on the BBN testbed.

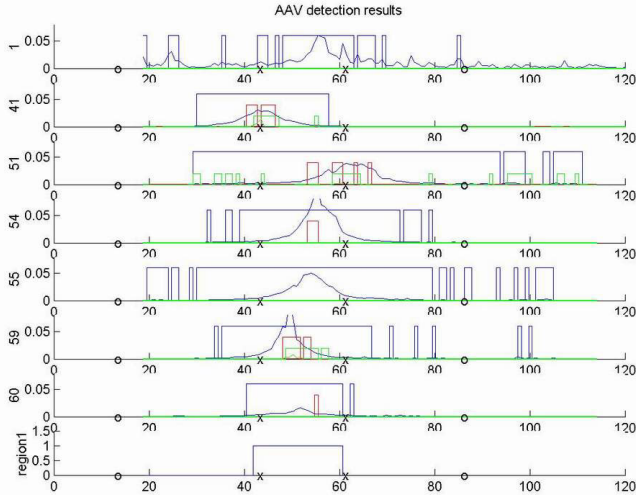


**Figure1:** Location of devices in the emulated sensor network.

Figure 1 shows the sensor network emulated in our evaluation. For the results presented here, data corresponds to a target AAV traversing the network from east to west on the road in the field. Since the target is expected to enter the field only from the east side, a region is initially created at the east end. The region contains devices labeled 1, 41, 51, 54, 56, 59, and 60. During the run, a second region will be created spanning the other devices.

Figure 2 shows the results of *NodeDet* and *DetFus* in the first region. In this run, we know from the ground truth that the target is in the geographic area of the region between times 42 and 60 (indicated by x in the graphs). The first seven graphs show the results by *NodeDet* in devices 1, 41, 51, 54, 56, 59, and 60, respectively. The energy values observed in acoustic, passive infrared, and seismic modalities are shown for each device. The detection result at each device is also shown (1 indicates target detection and 0 indicates no detection). The bottom curve shows the output of *DetFus*. Note that, it is 1 just prior target entering the region and stays 1 until after the target has left the region. In this run, the region detection results are excellent. However, depending on wind gusts and type of vehicles,

the detection results are not always this good. In other runs, we sometimes observe false detections (i.e., target detections when no target is present) and incomplete detections (i.e., no target detections when target is known to be present). The false detections and incomplete detections are in the range of 10% of the total number of detections.

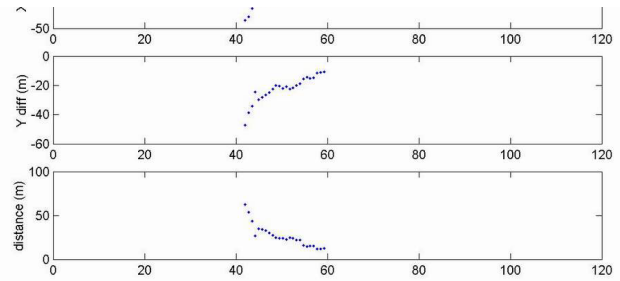


**Figure 2:** Target detection results for AAV moving through the sensor field.

Figure 3 shows the error in the location estimate from the *TarLoc* as compared to the ground truth. Note that, the error tends to decrease as the target traverses the region. The location estimation errors are in the range of 20-25 meters. Some of this error is also due to errors in the ground truth (since Global Positioning System location estimates of moving vehicles are known to have considerable errors). We are still evaluating the performance of our classification and target tracking algorithms. Results for these algorithms and those for other runs will be available at the project website <http://www.ece.wisc.edu/~sensit>.

## V. SUMMARY

In this paper, we presented an overview of our location-centric computing approach. A collaborative target tracking application using this approach was also described. Example results from a evaluation of this approach was also included. The results indicate that the location-centric approach is effective for collaborative signal processing in sensor networks.



**Figure 3:** Target localization errors in our application.

## ACKNOWLEDGMENTS AND DISCLAIMER

Professor Ramanathan's participation was partially supported by the Defense Advanced Research Projects Agency (DARPA) SensIT program under grant number F 30602-00-2-0555 and under the Emergent Surveillance Plexus MURI Award No. DAAD19-01-1-0504.

The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright annotation thereon.

Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the Defense Advanced Research Projects Agency (DARPA), Air Force Research Laboratory (AFRL), and Army Research Office (ARO).

The following team of faculty and students at University of Wisconsin, Madison contributed to the work described in this paper: Professors A. Sayeed, K. K. Saluja, and Y.-H. Hu, and graduate students K.-C. Wang, T.-L. Chin, T. Clouqueur, A. Ahtasham, A. D'Costa, X. Sheng, M. Duarte, V. Phipatansuphorn, and D. Li.

## REFERENCES

- [1] D. Li, K. Wong, Y. Hu and A. Sayeed. (2002) Detection, Classification, Tracking of Targets in Micro-sensor Networks, *IEEE Signal Processing Magazine*, pp. 17-29, March 2002.
- [2] P. Ramanathan, K.-C. Wang, K. K. Saluja, and T. Clouqueur, "Communication support for location-centric collaborative signal processing in sensor networks," *Proc. of DIMACS Workshop on Pervasive Networks*, May 2002.
- [3] T. Clouqueur, P. Ramanathan, K. Saluja and K.-C. Wang, Value-Fusion Versus Decision-Fusion for Fault-tolerance in Collaborative Target Detection in Sensor Networks, 4<sup>th</sup> Int. Conf. Information Fusion, Montreal, CA.